PARAMETRIC DECOMPOSITION OF OUTPUT GROWTH USING A STOCHASTIC INPUT DISTANCE FUNCTION

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This paper proposes a tractable approach for analyzing the sources of TFP changes (i.e., technical change, changes in technical and allocative inefficiency, and the scale effect) in a multi-output setting, while retaining the single-equation nature of the econometric procedure used to estimate the parameters of the underlying technology. The proposed approach relies on Bauer's cost function based decomposition of TFP changes and the duality between input distance and cost functions. The empirical results are based on a sample of 121 UK livestock farms observed over the period 1983-92 and a translog input distance function. It is found that improvements in technical efficiency appear to provide greater potential for enhancing farm returns than that which may be obtained from shifting the production frontier itself. In addition, scale economies and allocative inefficiency are also important sources for TFP changes on UK livestock farms.

Keywords: Cost function based decomposition of TFP, input distance function; UK livestock farms

Introduction

Several studies (i.e., Fan; Ahmad and Bravo-Ureta; Wu; Kalirajan, Obwona and Zhao; Kalirajan and Shand; Giannakas, Tran and Tzouvelekas; Giannakas, Schoney and Tzouvelekas) have attempted to explain and identify the sources of output growth in agriculture. By using a parametric production frontier approach, they have attributed output growth to factor accumulation (input growth), technical change, and changes in technical inefficiency.[1] Factor accumulation refers to movements along a path on or beneath the production frontier, technical change is associated with shifts in the production frontier, and changes in technical inefficiency are related to movements towards or away from the production frontier. Implicit in this framework, initiated by Nishimizu and Page, are the assumptions of constant returns to scale and of allocative efficiency.[2] Consequently, changes in total factor productivity (TFP) have been attributed to only two sources: technical change and changes in technical inefficiency. This however restricts unnecessarily the analysis of the potential sources of output growth.

Despite this limitation of previous studies, the parametric production frontier approach has two other shortcomings. *First*, it is unable to accommodate multi-output technologies, which are quite common in agricultural production. It is well known that inappropriate and unnecessary aggregation of outputs (and inputs) often results in misrepresentation of the structure of production, which may also affect the degree of technical efficiency. *Second*, even if input prices data are available, the effects of scale economies and of allocative inefficiency on TFP changes cannot be separated from each other (Bauer; Lovell).[3] Indeed, the scale effect can only be identified if input allocative efficiency is presumed, and in this case there is no need for input price data. In contrast, the effect of input allocative inefficiency cannot be identified even if the assumption of constant returns to scale is maintained. Thus, within the parametric production frontier approach, TFP changes may at most be attributed to changes in technical inefficiency, technical change, and the scale effect.[4] However, under the assumption of expected profit maximization, the parametric production frontier approach has the advantage of single-equation estimation and of requiring only input and output quantity data.[5]

On the other hand, cost frontiers can satisfactorily deal with decomposing TFP changes in the presence of multi-output technologies, input allocative inefficiency and non-constant returns to scale (Bauer). As long as panel data are available, this can be achieved by estimating a system of equations consisting of the cost frontier and the derived demand (or cost share) equations, which allows firm-specific and time-varying technical and allocative inefficiencies to be separated from each other (Kumbhakar and Lovell, 2000, pp. 166-75). Clearly, this is a more complicated econometric problem than single-equation estimation, and also requires firm specific data on input prices. Notice however that the effects of technical and allocative inefficiency cannot be identified separately if the cost frontier is estimated with a single-equation procedure.

The objective of this paper is to propose a tractable approach for analyzing the sources of TFP changes (i.e., technical change, changes in technical and allocative inefficiency, and the scale effect) in a multi-output setting, while retaining the single-equation nature of the econometric procedure used to estimate the parameters of the underlying technology. The proposed approach relies on Bauer's cost function based decomposition of TFP changes and the duality between input distance and cost functions. Specifically, the cost function (i.e., dual representation) is used for the theoretical decomposition of TFP changes whereas all necessary information for quantifying the sources of TFP changes are recovered from an econometrically estimated input distance function (i.e., primal representation). Thus, instead of using a system-wise procedure to estimate a cost frontier, all necessary information for decomposing TFP changes within a cost function approach can be recovered from an input distance function, which also fully describes the production technology.

In this context, the input distance function could be seen as an alternative that overcomes the shortcomings of production frontiers while retains the advantages of a single-equation estimation. By definition, the input distance function can easily accommodate multi-output technologies and thus has an obvious advantage over production frontiers. In addition, estimates of the input-oriented measure of technical inefficiency may be directly obtained from the estimated input distance function (Fare and Lovell). On the other hand, by using the duality between input distance and cost functions (e.g., Fare and Primont), it can be shown that the effects of scale economies and of allocative inefficiency on TFP changes can be separated from each other. The only assumption required to measure allocative efficiency from an input distance function is that one observed price equals the cost-minimizing price at the observed input mix (Fare and Grosskopf). However there is an endogeneity problem with input quantities in the single-equation estimation if the assumption of cost minimization is maintained. This problem may be solved by using an instrumental variable estimation procedure.

The rest of this paper is organized as follows: the theoretical framework is presented in the next section. The empirical model based on a translog input distance function and the estimation procedure utilizing an instrumental variable FGLS are described in the third section. Data sources and variables definition are discussed in the fourth section. The empirical results are analyzed in the fifth section. Concluding remarks follow in the last section.

Theoretical Framework

The input-oriented measure of productive efficiency may be defined as $E(Q,w,x,t) = C(Q,w,t)/C$ (Bauer; Lovell), where $0 < E(Q,w,x,t) \leq 1$, $C(Q,w;t)$ is a well-defined cost frontier function, C is the observed total cost, Q is a vector of output quantities, w is a vector of input prices, and t is a time index that serves as a proxy for technical change. $E(Q,w,x,t)$ is independent of input prices scaling and has a clear cost interpretation with $1-E(Q,w,x,t)$ indicating the percentage reduction in total cost if productive inefficiency is eliminated (Kopp).[6] Using Farrell's decomposition of efficiency, $E(Q,w,x,t) = T(Q,x,t) \cdot A(Q,w,x,t)$, where $T(Q,x,t) = 1/D^I(Q,x,t)$ and $A(Q,w,x,t) = \left[D^I(Q,x,t)C(Q,w,t)\right]/C$ are respectively the input-oriented measures of technical and allocative efficiency and $D^I(Q,x,t)$ is an input distance function that is non-decreasing, concave and linearly homogeneous in *x*, and non-increasing and convex in *Q*. By definition, $0 < T(Q,x,t) \leq 1$ and $0 < A(Q,w,x,t) \leq 1$, and both are independent of factor prices scaling and have an analogous cost interpretation.

By taking the logarithm of each side of $E(Q,w,x,t) = C(Q,w;t)/C$ and totally differentiating it with respect to t yields (Bauer):

$$\dot{E}(Q,w,x,t) = \sum_{k=1}^{h} \varepsilon_k^{CQ}(Q,w,t)\dot{Q}_k + \sum_{j=1}^{m} s_j(Q,w,t)\dot{w}_j + C^t(Q,w,t) - \dot{C}, \tag{1}$$

where a dot over a variable or function indicates its time rate of change, $\varepsilon_k^{CQ}(Q,w,t) = \partial \ln C(Q,w,t)/\partial \ln Q_k$, $s_j(Q,w,t) = \partial \ln C(Q,w,t)/\partial \ln w_j$, and $-C^t(Q,w,t) = \partial \ln C(Q,w,t)/\partial t$ is the rate of cost diminution. Alternatively, by taking the logarithm of $C = w'x$, and totally differentiating it with respect to t, yields:

$$\dot{C} = \sum_{j=1}^{m} s_j \dot{x}_j + \sum_{j=1}^{m} s_j \dot{w}_j . \tag{2}$$

Substituting (2) into (1) results in:

$$\dot{E}(Q,w,x,t) = \sum_{k=1}^{h} \varepsilon_k^{CQ}(Q,w,t)\dot{Q}_k + \sum_{j=1}^{m} s_j(Q,w,t)\dot{w}_j + C^t(Q,w,t) - \sum_{j=1}^{m} s_j \dot{x}_j - \sum_{j=1}^{m} s_j \dot{w}_j \tag{3}$$

Then, using the conventional Divisia index measure of TFP changes,

$$\dot{TFP} = \dot{Q} - \sum_{j=1}^{m} s_j \dot{x}_j = \sum_{k=1}^{h} R_k \dot{Q}_k - \sum_{j=1}^{m} s_j \dot{x}_j ,$$

where $R_k = p_k Q_k / TR$, p refers to output price and *TR* is observed revenue; the time rate of change of $E(Q,w,x,t) = T(Q,x,t) \cdot A(Q,w,x,t)$, i.e.,

$$\dot{E}(Q,w,x,t) = \dot{T}(Q,x,t) + \dot{A}(Q,w,x,t);$$

and by assuming marginal cost pricing

$$\sum_{k=1}^{h}\left(\frac{\varepsilon_k^{CQ}}{\sum \varepsilon_k^{CQ}}\right)\overset{\bullet}{Q}_k = \sum_{k=1}^{h}\left(\frac{p_k Q_k}{\sum p_k Q_k}\right)\overset{\bullet}{Q}_k = \sum_{k=1}^{h} R_k \overset{\bullet}{Q}_k = \overset{\bullet}{Q},$$

(3) may be rewritten as:

$$\overset{\bullet}{Q} = \sum_{j=1}^{m} s_j \overset{\bullet}{x}_j + \left[1 - \sum_{k=1}^{h} \varepsilon_k^{CQ}(Q,w,t)\right]\overset{\bullet}{Q} - C^t(Q,w,t) + \overset{\bullet}{T}(Q,x,t) + \\ + \overset{\bullet}{A}(Q,w,x,t) + \sum_{j=1}^{m}\left[s_j - s_j(Q,w,t)\right]\overset{\bullet}{w}_j, \qquad (4)$$

which is an output growth representation of the decomposition relationship developed by Bauer.

The first term in (4) captures the contribution of aggregate input growth on output changes over time (size effect).[7] The more essential an input is in the production process, the higher is its contribution to the size effect. The second term measures the relative contribution of scale economies to output growth (scale effect). This term vanishes under constant returns to scale as $\sum \varepsilon_k^{CQ}(Q,w,t) = 1$, while it is positive (negative) under increasing (decreasing) returns to scale, as long as aggregate input increases, and *vice versa*. The third term refers to the dual rate of technical change (cost diminution), which is positive (negative) under progressive (regressive) technical change.

The fourth and the fifth terms in (4) are positive (negative) as technical and allocative efficiency increases (decreases) over time. There is no *a priori* reason for both types of efficiency to increase or decrease simultaneously (Schmidt and Lovell) nor that their relative contribution should be of equal importance for output growth. More importantly, what really matters in output growth decomposition analysis is not the degree of efficiency itself, but its improvement over time. That is, even at low levels of productive efficiency, output gains may be achieved by improving either technical or allocative efficiency, or both. However, it seems difficult to achieve substantial output growth gains at very high levels of technical and/or allocative efficiency.

The last term in (4) is the price adjustment effect.[8] The existence of this term indicates that the aggregate measure of inputs is biased in the presence of allocative efficiency (Bauer). Under allocative efficiency, the price adjustment effect is equal to zero as $s_j = s_j(Q,w,t)$. Otherwise, its magnitude is inversely related to the degree of allocative efficiency. The price adjustment effect is also equal to zero when input prices change at the same rate, since $\sum\left[s_j - s_j(Q,w,t)\right] = 0$.

The next step concerns the recovery of all factors in (4) from an input distance function, through its duality with the cost function. *First*, Fare, Grosskopf and Lovell have shown that

$$\sum_{k=1}^{h} \varepsilon_k^{CQ}(Q,w,t) = \sum_{k=1}^{h} \frac{\partial \ln D^I(Q,x,t)}{\partial \ln Q_k}, \tag{5}$$

which provides the relationship for recovering the scale effect in (4) directly from the input distance function. *Second*, Atkinson and Cornwell have shown that

$$-C_t(Q,w,t) = -\frac{\partial \ln D^I(Q,x,t)}{\partial t}, \tag{6}$$

which relates the dual (cost diminution) with the primal (based on the input distance function) rate of technical change and also provides to the latter a clear cost saving interpretation.[9]

Third, $T(Q,x,t)$ is directly computed from $D^I(Q,x,t)$ as $T(Q,x,t) = 1/D^I$. *Fourth*, calculation of $A(Q,w,x,t)$ requires knowledge of minimum cost $C(Q,w,t)$, which can be computed as follows. Fare and Grosskopf have shown that

$$\frac{w_j}{C(Q,w,t)} = w_j^V(Q,x,t) = \frac{\partial D^I(Q,x,t)}{\partial x_j}, \tag{7}$$

where $w^V(Q,x,t)$ denotes the vector of virtual input prices. Virtual prices consist of that vector of input prices which makes the (observed) technically inefficient input mix allocativelly efficient; that is, virtual prices are interpreted as marginal products of inputs at the observed input mix (Grosskopf, Hayes and Hirschberg). However, in the presence of allocative inefficiency, observed input prices (w^O) do not necessarily coincide with the vector of cost minimizing input prices (w) for the observed input mix. Then, to compute $C(Q,w,t)$ from (7), it is required to assume that $w_j^O = w_j$ for one input.

Finally, the cost minimizing factor shares should be retrieved from the input distance function in order to compute the last term in (4). According to Bosco,

$$\frac{\partial \ln D^I(Q,x,t)}{\partial \ln x_j} = \frac{s_j(Q,w,t)}{D^I(Q,x,t)}\ , \tag{8a}$$

while Kim has shown that

$$\frac{\partial \ln w_l^V(Q,x,t)}{\partial \ln x_j} = s_j(Q,w,t)\left[\frac{D^I(Q,x,t)\left(\partial^2 D^I(Q,x,t)/\partial x_j \partial x_l\right)}{\left(\partial D^I(Q,x,t)/\partial x_j\right)\left(\partial D^I(Q,x,t)/\partial x_l\right)}\right]. \tag{8b}$$

Even though it can be shown that, after few manipulations, (8a) and (8b) are equal to each other, the former is used for the purposes of the present study.

Empirical Model and Estimation Procedure

Quantitative results of the output growth decomposition analysis presented in (4) can be obtained by econometrically estimating an input distance function. In order to keep the representation of production technology as flexible as possible within the parametric approach, the translog form is chosen to approximate the underlying input distance function (e.g., Grosskopf *et al*.; Coelli and Perelman, 1999, 2000):

$$\begin{aligned} \ln D_{it}^I(Q,x;t) = {} & \alpha_0 + \sum_{k=1}^{h} \alpha_k \ln Q_{kit} + \sum_{j=1}^{m} \beta_j \ln x_{jit} + \frac{1}{2}\sum_{k=1}^{h}\sum_{l=1}^{h} \alpha_{kl} \ln Q_{kit} \ln Q_{lit} + \\ & + \frac{1}{2}\sum_{j=1}^{m}\sum_{g=1}^{m} \beta_{jg} \ln x_{jit} \ln x_{git} + \sum_{j=1}^{m}\sum_{k=1}^{h} \delta_{jk} \ln Q_{kit} \ln x_{jit} + \\ & + \gamma_1 A(t) + \sum_{k=1}^{h} \varepsilon_k \ln Q_{kit} A(t) + \sum_{j=1}^{m} \theta_j \ln x_{jit} A(t) \end{aligned} \tag{9}$$

where subscript *i* is used to index farms and $A(t)$ corresponds to Baltagi and Griffin's general index of technical change defined as:

$$A(t) = \sum_{t=1}^{T} \lambda_t D_t \tag{10}$$

with D_t being time dummy for year *t* (*t*=1, …, *T*).[10] All λ_t (*t*=1, …, *T*) parameters are econometrically estimated by imposing the normalizing restrictions requiring that $\gamma_1=\gamma_2=1$ and $\lambda_1=0$ (Baltagi and Griffin). The regularity conditions associated with input distance function require homogeneity of degree one in input quantities and symmetry, which imply the following restrictions on the parameters of (9):

$$\sum_{j=1}^{m} \beta_j = 1 \text{ and } \sum_{j=1}^{m} \beta_{jg} = \sum_{j=1}^{m} \delta_{jk} = \sum_{j=1}^{m} \theta_i = 0 \tag{11}$$
$$\alpha_{kl} = \alpha_{lk} \text{ and } \beta_{jg} = \beta_{gj}$$

The homogeneity restrictions may also be imposed by dividing the left-hand side and all input quantities in the right-hand side of (9) by the quantity of that input used as a *numeraire*.

Based on (5), the scale elasticity for the translog input distance function is calculated as:

$$\sum_{k=1}^{h} \varepsilon_{kit}^{CQ} = -\left(\sum_{k=1}^{h} \alpha_k + \sum_{k=1}^{h} \sum_{l=1}^{h} \alpha_{kl} \ln Q_{kit} + \sum_{j=1}^{m} \sum_{k=1}^{h} \delta_{jk} \ln x_{jit} + \sum_{k=1}^{h} \varepsilon_k A(t) \right) . \tag{12}$$

The hypothesis of constant returns to scale can be tested by imposing the necessary restrictions associated with the linear homogeneity of the input distance function on output quantities. These restrictions are:

$$\sum_{k=1}^{h} \alpha_k = 1 \text{ and } \sum_{k=1}^{h} \alpha_{kl} = \sum_{j=1}^{k} \delta_{jk} = 0 .$$

If this hypothesis cannot be rejected, the underlying technology exhibits constant returns to scale and the second term in (4) vanishes.

On the other hand, by using (6) the dual and the primal rates of technical change are related to each other as follows:

$$-C_{it}^{t} = -[A(t) - A(t-1)]\left(1 + \sum_{k=1}^{h} \varepsilon_k \ln Q_{kit} + \sum_{j=1}^{m} \theta_j \ln x_{jit} \right), \tag{13}$$

where the latter can be decomposed into a pure component $[A(t) - A(t-1)]$ and a non-neutral component $[A(t) - A(t-1)]\left(\sum \varepsilon_k \ln Q_{kit} + \sum \theta_j \ln x_{jit}\right)$ that is farm-specific. The hypothesis of zero technical change can be tested by imposing the restriction that $\lambda_t=0\ \forall\ t\ (t=2,\ldots,T)$.[11] If the hypothesis of zero technical change cannot be rejected, the third term in (4) becomes equal to zero, and technical change has no effect on TFP changes.

In the case of the translog input distance function, there is no need to calculate virtual prices for the computation of allocative inefficiency and of cost minimizing factor shares. Given (7) and $A_{it}(Q,w,x;t) = \left[D_{it}^{I}(Q,x;t)C_{it}(Q,w;t)\right]/C_{it}$, $A_{it}(Q,w,x;t)$ $= s_{jit} \big/ \partial \ln D_{it}^{I}(Q,x;t) \big/ \partial \ln x_{jit}$, where $w_{jit}^{O} = w_{jit}$ for the j[th] input. Then,

$$\frac{\partial \ln D_{it}^{I}(Q,x;t)}{\partial \ln x_{jit}} = \beta_j + \sum_{g=1}^{m} \beta_{jg} \ln x_{git} + \sum_{k=1}^{h} \delta_{jk} \ln Q_{kit} + \theta_j A(t) \tag{14}$$

and $A_{it}(Q,w,x;t)$ and $s_{jit}(Q,w;t)$ for all *j* are computed by using (14) and (8a) along with the observed cost share of the input for which has been assumed that its cost minimizing price equals its observed price.

Given linear homogeneity, (9) may be written as $-\ln x_{jit} = \varphi(\bullet) - \ln D_{it}^{I}$ to obtain an estimable form of the input distance function, where *j* is the *numeraire* input and $\varphi(\bullet)$ is the right-hand side of (9) after dividing all inputs with the *numeraire* input. Since there are no observations for $\ln D_{it}^{I}$ and given that $\ln D_{it}^{I} \leq 0$, then $\ln D_{it}^{I} = -u_{it}$ (Grosskopf *et al.*; Coelli and Perelman, 1999, 2000), where u_{it} is a one-sided, non-negative error term representing the stochastic shortfall of the i[th] farm output from its production frontier due to the existence of technical inefficiency. Then, the stochastic input distance function model may be written as:

$$-\ln x_{jit} = \varphi(\bullet) + u_{it} + v_{it} \tag{15}$$

where v_{it} depicts a symmetric and normally distributed error term (i.e., statistical noise), representing a combination of those factors that cannot be controlled by farmers, omitted explanatory variables, and measurement errors in the dependent variable. It is also assumed that v_{it} and u_{it} are distributed independently of each other.

In the context of the present paper, the temporal pattern of the one-sided error term is important as the changes in technical efficiency over time rather than the degree of technical efficiency *per se* matters in (4). Cornwell, Schmidt and Sickles specification is adopted to model the temporal pattern of technical inefficiency through a quadratic function of time, i.e.,

$$u_{it} = \rho_{0i} + \rho_{1i}t + \rho_{2i}t^2, \qquad (16)$$

where $\rho_{0i}, \rho_{1i}, \rho_{2i}$ ($i = 1,...,n$) are farm-specific parameters to be estimated. Then, input-oriented technical efficiency is calculated as $T_{it} = \exp\left(\hat{u}_{it} - \max_i\{\hat{u}_{it}\}\right)$ for $\forall\ t$ ($t=1,...,T$), where a hat over a variable indicates its fitted values (Cornwell, Schmidt and Sickles).[12] The above specification is very flexible as it allows *first*, for farm-specific patterns of temporal variation; *second*, for testing the hypothesis of time invariant technical efficiency (i.e., $\rho_{1i} = \rho_{2i} = 0$ for $i = 1,...,n$), and *third*, for testing the existence of a common temporal pattern for all farms in the sample (i.e., $\rho_{1i} = \rho_1$ and $\rho_{2i} = \rho_2$ for $i = 1,...,n$). Farm-specific estimates of the change of technical efficiency over time are obtained as $\dot{T}_i = \rho_{1i} + 2\rho_{2i}t$ (Fecher and Pestieau).

Specifications (16) and (10) enable the effects of technical change and of time-varying technical efficiency changes on TFP growth to be identified separately in the absence of any distributional assumptions regarding the one-sided error term (Karagiannis, Midmore and Tzouvelekas). Since technical change and the temporal pattern of technical inefficiency are each captured through different variables, the identification problem mentioned by Kumbhakar, Heshmati and Hjalmarsson when (16) is accompanied with a single time trend representation of technical change is eliminated.[13] As a result, all the parameters associated with the rate of technical change in (13) and the temporal pattern of technical inefficiency in (16) are identified separately within a single-stage estimation procedure, which does not need to be maximum likelihood.

After substituting (9), (10) and (16) into (15) the resulting model is estimated by a single-equation estimation procedure using feasible generalized least squares (FGLS) as the variance of the error term is unknown. However, as the resulting model is non-linear in parameters, the procedure described in Kumbhakar and Hjalmarson (1995) should be applied.[14] Moreover, the random effect formulation is used to reduce the number of parameters to be estimated. In this case, the variance of statistical noise is estimated as $\sigma_v^2 = 1\big/N(T-1)\sum\sum(e_{it} - \bar{e}_i)^2$ and the variance of the one-sided error term as $\sigma_u^2 = 1/T\left(1/T(N-1)\sum\left(\sum e_i\right)^2 - \sigma_v^2\right)$, where e_{it} are the residuals of the non-linear OLS model and $\bar{e}_i = \sum e_{it} / T$. Then, FGLS estimates can be obtained by using non-linear OLS into a transformed model that arises by multiplying both sides of (15) by μ and then subtracting their means, where $\mu = 1 - \left(\sigma_v^2 / \left(\sigma_v^2 + T\sigma_u^2\right)\right)^{1/2}$.

Nevertheless, an endogeneity problem with input quantities is inherent in the single-equation estimation of an input distance function if the assumption of cost minimization is maintained. The endogeneity issue can ultimately be resolved by applying an instrumental variable procedure and estimate the resulting model with a non-linear instrumental variable FGLS. In order to be consistent with the theoretical framework of cost minimization, output quantities, input prices and the technology index are chosen as instruments. This consists an alternative approach to corrected ordinary least squares (Grosskopf *et al.*; Coelli and Perelman, 1999, 2000) and maximum likelihood (Morrison Paul, Johnston and Frengley) single-equation procedures for estimating input distance functions.

Data Description

Financial data from mixed livestock farm accounts are drawn from the *Farm Business Survey* (FBS) for England, Scotland, Wales and Northern Ireland (MAFF, 1994).[15] The FBS is an annual survey covering around 3,900 full time farms, selected from a random sample of census data that is stratified according to region, economic size, and type of farming.[16] The definition of the latter is based on standard gross margin (SGM) per hectare for crops and per head for livestock estimated for the period 1987 to 1989 (MAFF, 1994).[17] Farm classified as mixed livestock are those on which livestock products (beef, lamb and wool) account for more than two thirds of their total SGM.[18] Based on this, a total of 121 mixed livestock farms, observed for varying numbers of years, were extracted to form an unbalanced panel. The final panel data set consists of 1,069 observations, which in turn implies that on the average each farm is observed almost 9 times during the 1982-91 period.

The outputs included in the translog input distance function in (9) are: (*i*) the total annual production of live weight beef in kgs; (*ii*) the total annual production of live weight lamb in kgs; (*iii*) the total annual production of wool in kgs. The inputs included in the model are: (*i*) total agricultural *land* in hectares; (*ii*) total *labour*, comprising hired (permanent and casual), family and contract labour, measured in working hours; (*iii*) number of beef cows; (*iv*) the total number of sheep; and (*v*) purchased concentrated feed, coarse fodder and other livestock expenses (such as veterinary and medicine costs) measured in pounds sterling.

Data on input price movements are derived from annual indices published by the UK Department of the Environment, Food and Rural Affairs (formerly MAFF: see DEFRA). To the extent that these indices cover the entire UK, and are expressed as averages, some regional variation might cause bias, although since agricultural market integration and function are at a high level, this is not likely to be a significant source.

Empirical Results

The GLS parameter estimates of the translog input distance function are presented in Table 2. According to the estimated parameters, the translog input distance function is found, at the point of approximation, to be non-increasing in outputs and non-decreasing in inputs. Also, at the point of approximation, the Hessian matrix of the first and second-order partial derivatives with respect to inputs is found to be negative definite and the corresponding Hessian matrix with respect to outputs to be positive definite. These indicate respectively the concavity and convexity of the underlying input distance function with respect to inputs and outputs. The value of the adjusted R-squared indicates a satisfactory fit of translog specification.

The estimated variance of the one-side error term is found to be $\sigma_u^2 = 0.105$ and that of the statistical noise $\sigma_v^2 = 0.013$. The presence of technical inefficiency is related to the statistical significance of σ_u^2. If $\sigma_u^2 = 0$ then the least squares estimator is best linear unbiased and farm-effects are zero. This hypothesis can be tested with the following LM-test statistic $\lambda = \frac{NT}{2(T-1)}\left[\left(\sum_i^N\left(\sum_t^T \varepsilon_{it}\right)^2 \Big/ \sum_i^N\sum_t^T \varepsilon_{it}^2\right) - 1\right]^2$, which is asymptotically distributed as χ^2 with one degree of freedom (Breusch and Pagan). The null hypothesis that $\sigma_u^2 = 0$ is rejected at the 5% level of significance (see Table 3) indicating that the technical inefficiency effects are in fact stochastic. Thus, a significant part of output variability among livestock farms in explained by the existing differences in the degree of technical efficiency.

The hypothesis that technical inefficiency is time-invariant is also rejected at the 5% level of significance (see Table 3). This means that output growth has been affected by changes in the degree of technical efficiency over time. During the period

1983-92, technical efficiency tended to increase over time, as the most of the estimated ρ parameters are positive.[19] Specifically, mean input-oriented technical efficiency increased from 78.80% in 1983 to 84.73% in 1992 (see Table 4), implying that its contribution into output growth would positive. During the period 1983-92, the average annual rate of increase in technical efficiency is estimated to be 0.66%. The vast majority of livestock farms in the sample have consistently achieved scores of technical efficiency greater than 60% during the period 1983-92. However, the portion of livestock farms with technical efficiency scores below 60% decreased over time. This means that the portion of livestock farms facing significant technical inefficiency problems has been decreased. The estimated mean technical efficiency was found to be 82.77% during the period 1983-1992. Thus, on average, a 17.23% decrease in total cost could have been achieved during this period, without altering the total volume of outputs, production technology and input usage.

Mean allocative efficiency is found to be 53.85% during the period 1983-92 (see Table 4), implying that UK livestock farms in the sample have achieved a relatively poor allocation of existing resources. As a result, a 46.15% decrease in cost should be feasible by means of a further re-allocation of inputs for any given level of outputs. The great majority of farmers in the sample have consistently achieved scores of allocative efficiency less than 60%. This portion tended however to remain rather stable over time. Mean allocative efficiency is smaller than the corresponding point estimate of technical efficiency, indicating that livestock farms in UK did better in achieving the maximum attainable outputs for given inputs than in allocating existing resources. Allocative efficiency increased slightly from 49.51% in 1983 to 50.78% in 1992 (see Table 4). In particular, allocative efficiency increased during the period 1983-92 with an average annual rate of 0.14%. Thus, allocative efficiency also tended to contribute positively to both TFP and output growth. However, the average rate of change of allocative efficiency is lower than that of technical efficiency and thus, its relative contribution to output growth is expected to be relatively smaller.

Mean productive efficiency was found to be 44.35% (see Table 4). This figure represents the ratio of minimum to actual cost of production and implies that significant cost savings (about 45.65%) may be achieved by improving both technical and allocative efficiency. Only a very small portion of farms in the sample achieved a score greater than 80%. Given the estimates of technical and allocative inefficiency, productive inefficiency is mostly due allocative inefficiency. Productive efficiency increased over time from 37.85% in 1983 to 42.83% in 1993. Nevertheless, its annual rate of increase (0.55%) is greater than that of allocative efficiency as technical inefficiency tended to increase at a higher rate.

The decomposition analysis results for UK livestock farms' output growth during the period 1983-1992 are given in Table 5. An average annual rate of 1.93% is observed for output growth. This growth stems mainly from the corresponding increase in sheep meat (1.72%) and wool (0.46%), whereas cattle output exhibits a decrease during the same period of -0.26%.[20] Our empirical findings suggest that most of output growth (59.5%) in livestock production is due to input increase. A smaller portion is attributed to productivity growth, which grew with an average annual rate of 0.96%. Thus, substantial output increases may still be achieved *ceteris paribus* by improving TFP, and this has important policy implications as far as the sources of productivity growth are identified.

Since the hypothesis of zero technical change is rejected at the 5% level of significance (see Table 3), the effect of technical change should be taken into account in (4). Parameter estimates indicate technological progress, which on the average was 0.20%. However, in contrast to most previous studies, technical change has not been the main source of TFP growth, accounting for only 20.70% of TFP growth and 10.40% of output growth (see Table 5). Moreover, the hypothesis of Hicks neutral technical change is rejected at the 5% level of significance (see Table 3). The non-neutral component dominates the neutral component although the latter exhibits complex and erratic patterns of technical change consisting of bursts of rapid changes and periods of stagnation. Specifically, the non-neutral component is on the average 0.18% ranging between a maximum of 0.41% in 1988 and a minimum of 0.02% in 1984, whereas the neutral component while is on the average only 0.02% it ranges from a maximum of 3.25% in 1989 and a minimum of -4.06% in 1987.

On the other hand, the hypothesis of constant returns to scale is also rejected at the 5% level of significance (see Table 3). Thus, the scale effect has contributed to TFP changes and output growth. In particular, the scale effect is positive as livestock farms in UK exhibited increasing returns to scale and the aggregate output index increased over time. On average, the degree of scale economies is estimated at 1.29 during the period 1983-92. As a result, economies of scale enhanced annual output growth by an average annual rate of 0.15% (see Table 5). In relative terms, the scale effect is the third larger factor influencing TFP and output growth, after technical efficiency and technological progress. This rather significant figure would have been omitted if constant returns to scale were falsely assumed.

Technical and allocative inefficiencies have affected TFP and output growth in the same manner. The relative contribution of each depends on their rate of change over time, rather than their absolute magnitude. As shown in Table 5, the relative contribution of the allocative efficiency effect on output growth is less than that of technical efficiency, since the average rate of increase of the former was found to be lower than that of the latter. Moreover, changes in technical efficiency are found to be the main source of TFP and output change. Overall, productive efficiency accounts for 83.3% of annual TFP growth and for 41.5% of average annual output growth among livestock farms in UK.

The price adjustment effect was found to have a relatively significant impact on TFP and output growth. On average, the price adjustment effect accounted for 19.6% of output slowdown. However, given the existence of allocative inefficiency, its impact cannot be neglected in attempting to measure the TFP growth rate accurately. After accounting for all theoretically proposed sources of TFP growth and for the size effect, a -9.1% of observed output growth remained unexplained. Nevertheless, the unexplained portion of output growth is smaller than the unexplained residual that would have been obtained by using a production approach (e.g., Ahmad and Bravo-Ureta), which does not separate the scale and the allocative inefficiency effects.[21]

Concluding Remarks

The development of the distance function approach finally provides a more realistic framework for parametric decomposition of output growth appropriate to the multi-input, multi-output context of the farm business. Separate identification of the effects for cattle, sheep and wool on British livestock farms will have substantial implications for the development of agricultural policy, since improvements in technical and allocative efficiency appear, on the evidence presented by this study, to provide greater potential for the improvement of farm returns than that which may be obtained from shifting the production frontier itself. This is especially important where technical changes are implicated in a decline in the environmental quality of the agro-ecosystem, since a large (and growing) number of farms in the sample analysed could improve both technical and allocative efficiency.

Table 1. Summary Statistics of the Variables

Variable	Mean	Min	Max	StDev
Outputs				
Beef (animals)	71	2	724	58
Lamb (kgs)	616	4	3.839	457
Wool (kgs)	1.362	17	11.430	1.018
Inputs				
Cattle (animals)	129	3	827	106
Sheep (animals)	667	10	2.689	451
Labour (working hours)	5.254	1.806	17.727	2.415
Land (acres)	156	28	944	137
Machinery (GB pounds)	9.034	612	59.999	6.808
Materials (GB pounds)	13.723	428	108.219	12.476
Other Cost (GB pounds)	15.150	664	113.559	14.098

Table 2. Parameter Estimates of the Translog Input Distance Function

Parameter	Estimate	Std Error	Parameter	Estimate	Std Error
α_B	-0.173	(0.071)*	β_{SF}	0.106	(0.043)*
α_L	-0.283	(0.079)*	β_{SS}	-0.177	(0.047)*
α_W	-0.446	(0.082)*	β_{EA}	0.280	
β_C	0.066	(0.029)**	β_{EM}	0.017	(0.091)
β_S	0.322	(0.090)*	β_{EF}	-0.082	(0.043)**
β_E	0.155	(0.078)**	β_{EE}	0.104	(0.048)*
β_A	0.054		β_{AM}	0.082	
β_M	0.224	(0.035)*	β_{AF}	0.009	
β_F	0.178	(0.057)*	β_{AA}	-0.335	
λ_2	-0.015	(0.031)	β_{MF}	0.049	(0.059)
λ_3	-0.050	(0.021)*	β_{MM}	0.038	(0.042)
λ_4	-0.024	(0.035)	β_{FF}	0.114	(0.029)*
λ_5	-0.465	(0.135)*	θ_{CT}	0.021	(0.008)*
λ_6	-0.276	(0.109)*	θ_{ST}	0.034	(0.009)*
λ_7	0.238	(0.121)**	θ_{ET}	-0.015	(0.033)
λ_8	0.044	(0.041)	θ_{AT}	0.011	
λ_9	0.136	(0.065)**	θ_{MT}	-0.011	(0.006)**
λ_{10}	0.904	(0.201)*	θ_{FT}	-0.020	(0.045)
α_{BL}	-0.008	(0.057)	δ_{CB}	0.024	(0.045)
α_{BW}	0.256	(0.059)*	δ_{CL}	-0.117	(0.046)*
α_{BB}	-0.073	(0.030)*	δ_{CW}	-0.058	(0.081)
α_{LW}	-0.324	(0.055)*	δ_{SB}	-0.285	(0.070)*
α_{LL}	0.085	(0.037)*	δ_{SL}	0.130	(0.054)*
α_{WW}	0.008	(0.025)	δ_{SW}	0.238	(0.065)*
ε_{BT}	0.034	(0.071)	δ_{EB}	-0.008	(0.087)
ε_{LT}	-0.039	(0.019)**	δ_{EL}	-0.329	(0.099)*
ε_{WT}	0.061	(0.082)	δ_{EW}	0.335	(0.097)*
β_{CS}	0.366	(0.086)*	δ_{AB}	0.158	
β_{CE}	-0.267	(0.100)*	δ_{AL}	0.033	
β_{CA}	0.041		δ_{AW}	0.192	
β_{CM}	-0.033	(0.078)	δ_{MB}	0.006	(0.006)
β_{CF}	-0.196	(0.055)*	δ_{ML}	0.260	(0.077)*
β_{CC}	0.089	(0.026)*	δ_{MW}	-0.106	(0.062)**
β_{SE}	-0.058	(0.105)	δ_{FB}	0.105	(0.043)*
β_{SA}	-0.083		δ_{FL}	0.017	(0.054)
β_{SM}	-0.154	(0.065)*	δ_{FW}	-0.217	(0.052)*
$\bar{R}^2$	0.878				

Notes: (1) B refers to beef live weight, L to lamb weight, W: to wool, C: to cattle, S: to sheep, E to labor, A to area, M to machinery, and F :to materials.
(2) $^{*(**)}$ indicates statistical significance at the 1(5)% level.
(3) Estimated parameters without standard errors are computed using the homogeneity property.

Table 3. Model Specification Tests

Hypothesis	Test Statistic	Critical Value (α=0.05)
Technical Efficiency ($\sigma_u^2 = 0$)	18.51	3.84
Time-Invariant Technical Inefficiency $\left(\rho_{i1} = 0 \,\&\, \rho_{i2} = 0 \ \forall \mathrm{i}\right)$	295.3	$\chi^2_{242} \approx 232$
Zero Technical Change $\left(\lambda_t = 0 \ \forall t\right)$	52.58	$\chi^2_9 = 16.92$
Hicks-Neutral Technical Change $\left(\varepsilon_k = 0 \,\&\, \theta_j = 0 \ \forall \mathrm{k}, \mathrm{j}\right)$	34.71	$\chi^2_9 = 16.92$
Constant Returns to Scale $\left(\sum \alpha_k = 1, \sum \alpha_{kl} = 0, \sum \delta_{jk} = 0\right)$	29.06	$\chi^2_{10} = 18.31$

Table 4. Frequency Distribution of Technical, Allocative and Productive Efficiency.

	1983	1984	1985	1986	1987	1988	1989	1990	1991	1992
Technical Efficiency										
<20	0	0	0	0	0	0	0	0	0	0
20-30	0	0	1	0	0	0	1	0	0	0
30-40	4	4	4	4	1	3	1	0	2	1
40-50	3	4	5	7	6	7	9	5	4	0
50-60	11	7	6	6	9	7	9	7	3	2
60-70	11	7	8	12	9	9	6	7	7	9
70-80	14	10	16	9	17	10	8	11	13	8
80-90	14	26	30	30	22	26	29	21	16	12
>90	39	53	51	53	57	58	57	55	44	29
Mean	78.80	83.00	82.18	82.27	82.83	82.61	82.37	85.38	83.48	84.73
Allocative Efficiency										
<20	0	1	1	1	1	2	2	0	1	1
20-30	5	10	11	10	8	7	9	6	7	1
30-40	27	18	21	22	22	16	19	21	12	13
40-50	19	23	23	22	23	20	18	16	14	10
50-60	6	12	11	16	13	15	21	15	12	5
60-70	7	7	9	10	5	7	4	4	3	5
70-80	2	2	6	8	10	6	3	5	1	1
80-90	2	4	2	0	6	5	4	0	4	2
>90	2	0	1	3	0	7	3	4	2	2
Mean	49.51	53.64	52.61	55.74	53.06	55.68	54.17	57.63	55.68	50.78
Cost Efficiency										
<20	16	8	12	11	12	11	13	6	7	4
20-30	22	17	16	17	15	13	16	12	9	6
30-40	19	19	23	23	19	14	16	21	15	14
40-50	9	20	20	21	24	20	22	15	15	5
50-60	5	10	9	9	8	14	10	9	4	5
60-70	0	1	2	4	3	6	2	3	1	2
70-80	1	2	2	5	5	2	1	3	2	2
80-90	2	2	0	1	3	0	3	1	3	3
>90	1	0	2	3	1	5	2	2	2	0
Mean	37.85	44.06	42.78	46.46	44.06	45.24	44.37	49.16	46.67	42.83

Table 5. Decomposition of Output Growth (average values for the 1983-92 period)

	Average Annual Rate of Change	Percentage
Aggregate Output Growth	1.93	100
of which:		
Cattle	-0.26	-13.4
Sheep	1.72	89.3
Wool	0.46	24.1
Aggregate Input Growth	1.15	59.5
of which:		
Cattle herd	-0.19	-16.9
Sheep herd	0.25	21.9
Labour	-0.04	-3.9
Area	-0.25	-21.7
Machinery	0.56	49.0
Materials	0.82	71.6
Total Factor Productivity Growth	0.96	49.7
of which:		
Rate of Technical Change	0.20	20.7
Scale Effect	0.15	15.3
Change in Technical Efficiency	0.66	69.0
Change in Allocative Efficiency	0.14	14.6
Price Adjustment Effect	-0.19	-19.6
Unexplained Residual	-0.18	-9.1

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Endnotes

[1] A notable exception is a recent paper by Karagiannis and Tzouvelekas (2001) that also takes into account the effects of scale economies and allocative inefficiency, but in the cost of using self-dual (i.e., Cobb-Douglas) production frontiers.

[2] The former however is not always evident from the empirical results reported on the aforementioned studies. For example, Fan, Ahmad and Bravo-Ureta, and Giannakas, Schoney and Tzouvelekas found increasing returns to scale while Wu and Giannakas, Tran and Tzouvelekas reported decreasing returns to scale.

[3] When input price data are available, Kumbhakar (2000) has been able to incorporate a price effect into decomposition of TFP changes, which captures either deviations of input prices form the value of their marginal products or departures of marginal rate of technical substitution from the ratio of input prices.

[4] The non-parametric approach can provide a similar decomposition in a multi-output setting based on the Malmquist TFP index, which however cannot account for the extent of allocative inefficiency since it is a primal concept (Tauer, 1998).

[5] A single-equation estimation of a production frontier function is in general incapable of providing estimates of allocative inefficiency. This is not true only in the limited case of self-dual functions (Bravo-Ureta and Rieger).

[6] That is, scaling all factor prices equally or each factor price individually will have no effect on the input-oriented measure of inefficiency. This property of input-oriented measures is due to their radial nature and it will be proved important in panel data studies where there are no price data for individual producers. Apparently, it allows the use of regional, or even national, price data to be used in estimating efficiency measures, without altering the final outcome.

[7] Aggregate input growth is measured as a Divisia index; this follows directly from the definition of TFP in terms of Divisia index. The fact that actual (observed) factor cost shares are used as weights of individual input growth gives rise to the sixth term in (4).

[8] The existence of the price adjustment effect is closely related to the definition of TFP, which is based on observed input and output quantities.

[9] Notice that both scale elasticity and rate of technical change should be evaluated at the frontier (Forsund; Atkinson and Cornwell).

[10] Since $A(t)^2$ is equal to *A(t)*, (9) does not contain a square term for technical change.

[11] The non-neutral component is different than zero only if the neutral component is different than zero (Baltagi and Griffin). Consequently, if *A(t)* is unchanged, changes in input or output quantities have no effect on the rate of technical change.

[12] This normalization is necessary to ensure the non-negativity of u_{it}, which in turn indicates that every year there is at least one farm that lies on the production frontier.

[13] Following Kumbhakar, Heshmati and Hjalmarsson argument the decomposition results of Ahmad and Bravo-Ureta, Wu and Giannakas, Tran and Tzouvelekas should be seen with caution as both technical change and time-varying technical efficiency are modelled via a single time trend.

[14] It can be seen that the resulting model is linear in estimated parameters by assuming Hicks-neutral technical change.

[15] Grateful acknowledgement is made to MAFF, for permission to use data from the Farm Business Survey, provided through the ESRC Data Archive at the University of Essex.

[16] The FBS is similar, but apparently not the same, with the EU's Farm Accounting Data Network (FADN), with the main difference being on the classification of farms according to the type of farming. More details can be found on MAFF (1994).

[17] The SGM is a financial measure based on the concept of the gross margin for farming enterprises. Because information on gross margin is not available for each farm, standards or norms have been calculated for all of the major crop and livestock enterprises (MAFF, 1994).

[18] The total SGM for each farm is calculated by multiplying its crop area and livestock numbers by the appropriate SGM coefficients and then summing the result for all enterprises on the farm (MAFF, 1994).

[19] To conserve space estimates of the ρ parameters are not reported herein, but are available from the authors upon request.

[20] Note that although this was prior to the Parliamentary announcement of a possible link between BSE and vCJD in humans, consumer resistance was already developing to beef products at this stage.

[21] A similar comparison with Fan or Kalirajan, Obwona and Zhao, and Kalirajan and Shand is not possible as technical change and the size effect are respectively calculated in a residual manner.